SHORT-TERM LOAD FORECAST IN ELECTRIC ENERGY SYSTEM IN BULGARIA

Irina ASENOVA[1], *Dimitar GEORGIEV*[2]

[1] Dept. of Electrical Engineering, University of Transport, Street G. Milev 158, 1574 Sofia, Bulgaria
[2] Dept. of Power Engineering and Electrical Equipment, University of Transport, Street G. Milev 158, 1574 Sofia, Bulgaria

Irka_honey@yahoo.com , Mitko_honney@yahoo.com

Abstract. *As the accuracy of the electricity load forecast is crucial in providing better cost effective risk management plans, this paper proposes a Short Term Electricity Load Forecast (STLF) model with high forecasting accuracy. Two kind of neural networks, Multilayer Perceptron network model and Radial Basis Function network model, are presented and compared using the mean absolute percentage error. The data used in the models are electricity load historical data. Even though the very good performance of the used model for the load data, weather parameters, especially the temperature, take important part for the energy predicting which is taken into account in this paper. A comparative evaluation between a traditional statistical method and artificial neural networks is presented.*

Keywords

Neural Networks, Electrical energy system, Load forecasting.

1. Introduction

Electricity load prediction is a main task, as during the planning, as well during the electrical system management. In the base of forecasting models find application different approaches [1, 2]. In the recent years many researchers switched to try the modern techniques based on artificial intelligence. Of all, the Artificial Neural Network (ANN) receives the most attention [3]. The reason for its popularity is its easy of use and its ability to learn complex input-output relationship. This gives better performance in capturing nonlinearities for a time series signal used in time series prediction.

The main objective of the power utility is to generate electric power to satisfy consumer's energy obtained at all times and at minimum cost. This objective can be met only if the power utility is based on advance knowledge of the load demand on short, medium and long term basis.

The electrical load prediction period may be a month or a year for the medium and long term forecasts [4]; and a day or an hour for the short term forecasts [5]. The short term load forecast is needed for control, security assessment, unit commitment, optimum planning of power generation, planning of energy exchange.

This paper deals with a methodology approach, based on ANN, to forecast next 24 hour load. A climatic variable is taken into account to help the ANN capturing the periodic behavior of load.

The rest of the paper is organized as follows: Section 2 describes a vector of input variables; Section 3 presents and discusses the results, and gives a comparative evaluation of the methods used for the energy forecasting. Finally, Section 4 presents some concluding remarks and proposal for further work.

2. Vector of Input Variables

The data set used in this research for developing the models was obtained from National Central dispatching control of Bulgaria [6] during six consecutive years from 2002 to 2007. In the presented paper, artificial neural networks are used for the mean monthly hour load forecast. The input variables to the networks present the average monthly hour load, which distribution is shown in fig. 1.

The daily temperature data per every 3 hours for the same period of time was taken by the Meteorology website [7]. The set of temperature data used in the evaluation was calculated as the average monthly temperature per every 3 hours. Its distribution is presented in fig. 2.

Once the input variables are selected, time series are processed to give zero mean and unit variance. From all ANN models trained and tested, the most appropriate two kinds of neural network models are chosen and compared: Multilayer Perceptron (MLP) network model and Radial Basis Function (RBF) network model. An MLP is composed of a layered arrangement of artificial neurons in

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which each neuron of a given layer feeds all neurons of the next layer. It is used a feed forward type neural networks, consisting of one hidden layer. Back propagation algorithm is utilized for training the MLP network.

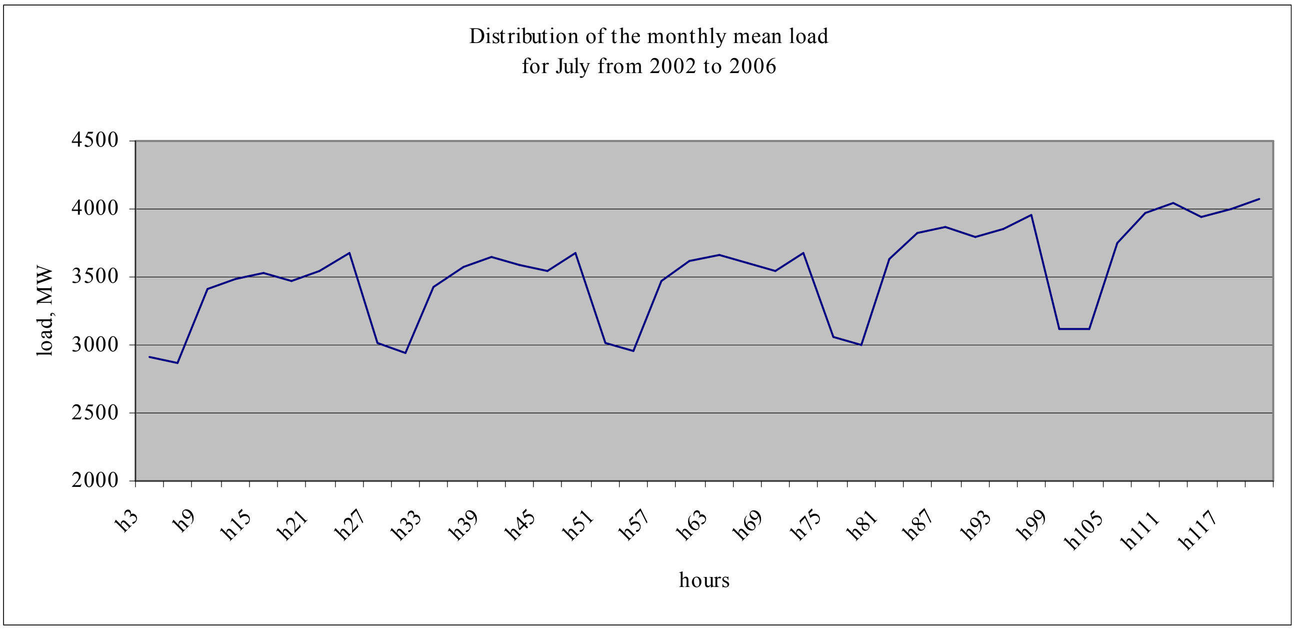

Fig. 1. Distribution of the monthly mean load consumption for July from 2002 to 2006.

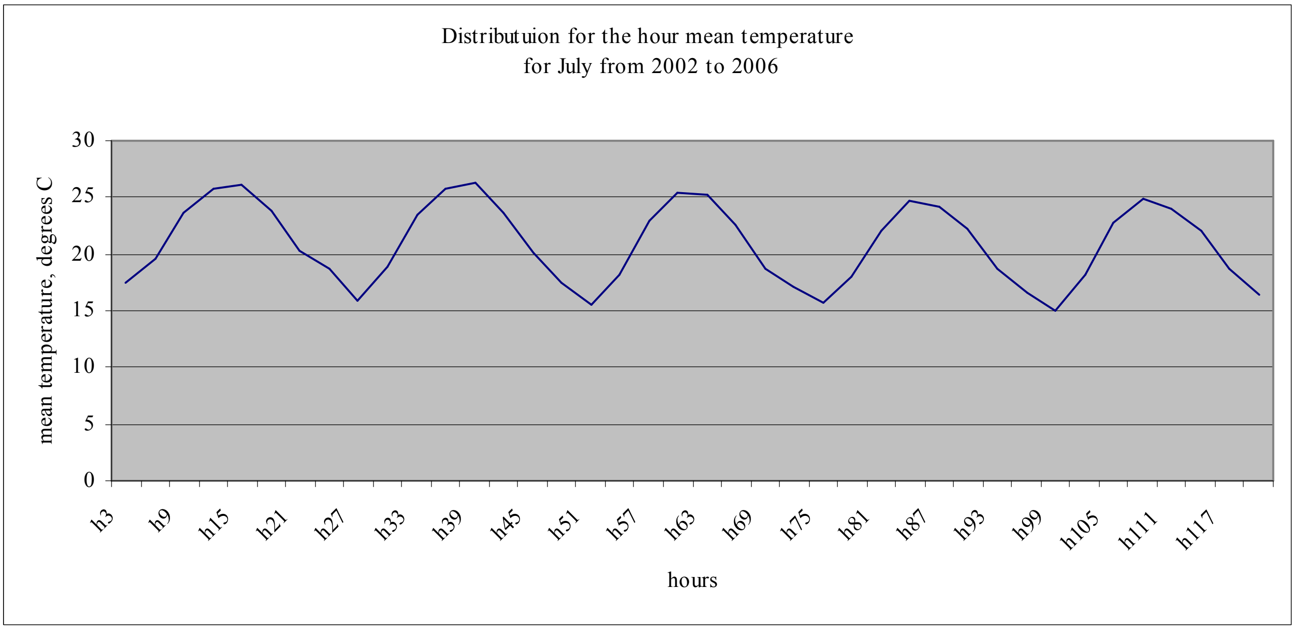

Fig. 2. Distribution of the monthly mean temperature for July from 2002 to 2006.

The training error level is set to 10^{-4}. The optimal number of hidden neurons is obtained experimentally by changing the network design and running the training process several times until a very good performance was obtained. RBF neural networks exhibit a very good performance and learning ability. The RBF neural model is a 3-layer feed - forward network with linear transfer function for the output layer and Gaussian function (radial basis function) for the hidden layer.

The two successful models are evaluated, based on the prediction error values. Because SD ratio doesn't depend on the sign, it is used for error comparison.

3. Results and discussions

3.1 Forecast simulation results

Taking into account the input variables a correlation between them is found. A monthly distribution of the load as a function of the monthly average effective temperature, for all days over the years from 2002 to 2006 is presented in fig. 3. It can be seen that the minimum of the energy consumption is smallest at 22,25 degrees C.

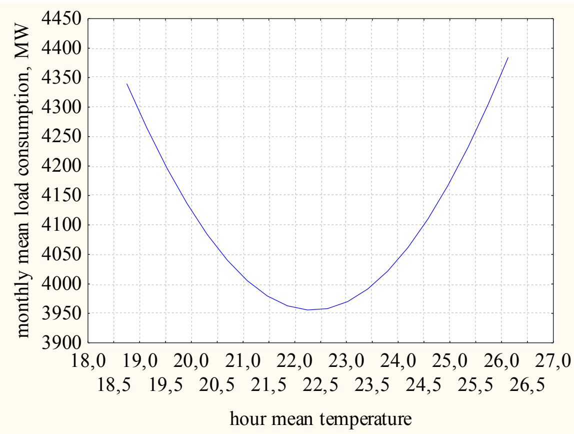

Fig. 3. Correlation between the load and the monthly average effective temperature.

The proposed two models are tested with sets of historical data, containing the electricity average month hour load for July 2007. The results P_{MLP}^{ANN} and P_{RBF}^{ANN} are presented in tab. 1.

The most significant indicator for the performance of the forecast ANN model, as is generally accepted for comparing different forecast approaches, is the mean absolute percentage error (MAPE) which is defined as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|x_i - y_i|}{x_i}\right) 100\ \%, \qquad (1)$$

where N is the number of points measured, x is the actual values(target) and y is the predicted values.

Tab. 1. Forecast results and errors obtained with MLP and RBF neural models

Hour	P_{07}	P_{07}^{MLP}	P_{07}^{RBF}	δ_{07}^{MLP}	δ_{07}^{RBF}
	MW	MW	MW	%	%
3	3382	3308	3351	2,18	0,91
6	3304	3306	3304	0,06	0,00
9	4011	4028	4027	0,42	0,39
12	4318	4304	4285	0,32	0,76
15	4376	4324	4373	1,18	0,06
18	4269	4268	4281	0,02	0,28
21	4261	4331	4251	1,64	0,23
24	4340	4340	4396	0,00	1,29
mean absolute percentage error, %				**0,73**	**0,49**

Figure 1 shows the actual and predicted load curves via MLP and RBF taking into account the weather parameter.

The forecast results and errors obtained with MLP and RBF neural models are in accordance with the expectable values. The forecast results also confirm the conclusion made in [8], namely that RBF neural model has the best performance for the load data presented.

3.2 A comparative evaluation of models for the load prediction

It is difficult to make an exact comparative study with different approaches. In fact, there are many factors influencing the design of the model. Therefore, the following comparative study is based solely on the test of the different three models for the same period of time: traditional statistical method based on time series analysis; RBF neural model without taking into account of the weather parameters; and RBF neural model taking into account of the weather parameters.

The results, P_{07}^{Stat} and P_{07}^{ANN}, for the load forecast performed by traditional statistical method, and the ANN neural model without taking into account of the average monthly hour temperature T, are presented in tab. 2, respectively. The results P_{07}^{RBF} for the load forecast using the RBF(t) neural model taking into account of T also is given in tab. 2.

Tab. 2. Comparative forecast results and errors

Hour	P_{07}	P_{07}^{Stat}	P_{07}^{ANN}	P_{07}^{RBF}	δ_{07}^{Stat}	δ_{07}^{ANN}	δ_{07}^{RBF}
	MW	MW	MW	MW	%	%	%
3	3382	3380	3382	3351	0,06	0	0,91
6	3304	3308	3353	3304	0,1	1,48	0
9	4011	3853	3990	4027	3,9	0,52	0,39
12	4318	4001	4305	4285	7,34	0,3	0,76
15	4376	4033	4376	4373	7,84	0	0,06
18	4269	3956	4300	4281	7,32	0,72	0,28
21	4261	3961	4380	4251	7,04	2,79	0,23
24	4340	4088	4340	4396	5,8	0	1,29
mean absolute percentage error, %					**4,92**	**0,73**	**0,49**

The error values in tab. 2 show satisfactory approximation between the target values and the results of the forecast in the first model. It can be seen, that the MAPE value is better in the second model. The usual discrepancies may still be found between the target values and the forecast results, as is noticeable, when considering the two input variables together: the mean monthly load consumption and the mean monthly temperature. These differences are more expressive at the peak load hours.

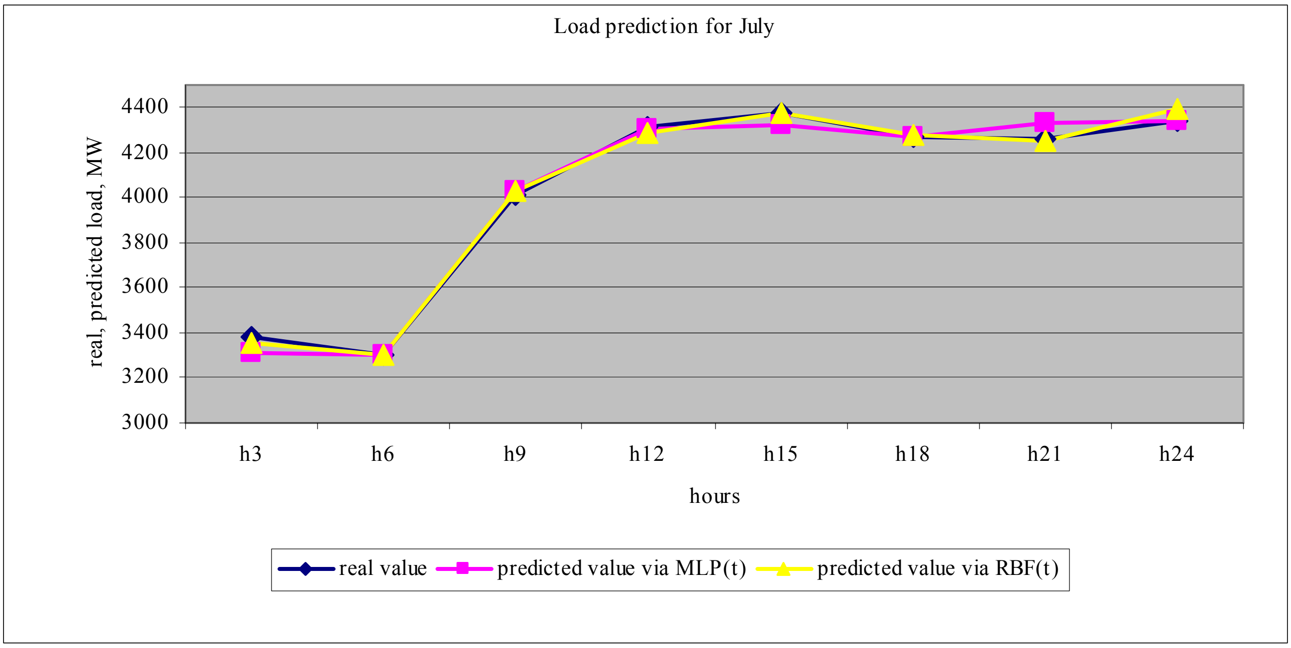

Fig. 4. Load prediction for July.

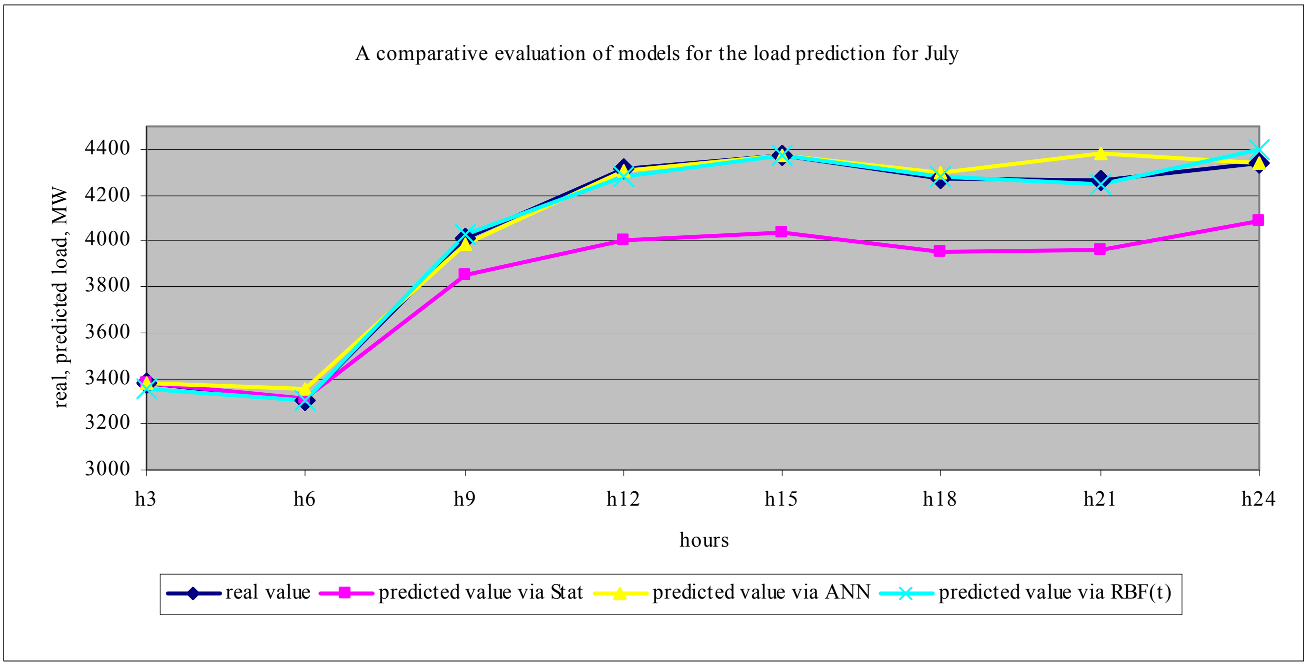

Fig. 5. A comparative evaluation of models for the load prediction.

Figure 5 shows the target and predicted load curves via the traditional statistical method Stat, ANN model without taking into account of the temperature and RBF, presenting the temperature influence on the forecast results.

From this comparative evaluation of models for the load prediction follows that the best model, giving very good performance, is the RBF neural model using the temperature as an input vector together with the historical load data.

4. Conclusion

STLF has an important role in the electricity distribution sector, aiding in decision-making in actions like control and management of networks. The ANN, as a methodology form short-term forecast, has been widely used with very good results. However, there is always some arbitrariness in the choice of the variables that make up the input vector. To reduce this arbitrariness, the average monthly temperature per every 3 hours has been used as an input vector.

A comparative evaluation of models for the load prediction is presented. The forecasting results using this kind of input variable vector were compared with the results gotten by the traditional statistical method based on time series analysis, and RBF neural model without taking into account of the weather parameters. As can be noted from the comparative evaluation of models for the load prediction, the best model, giving very good performance, is the RBF neural model using the temperature as an input vector. MLP neural model, taking into account the mean monthly hourly temperature gives forecast results with the same mean absolute percentage error as the results received using RBF neural model presented in [8].

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About Authors

Irina ASENOVA was born in 1961. She received her M.Sc. from Technical University in Sofia in 1985, and doctorate in 2008. Her research interests include load forecast in the electrical energy system, symbolic sensitivity analysis of the transfer function with respect to parameters in analog circuits using nullor models and Coates flow graphs.

Dimitar GEORGIEV was born in 1985. He graduated Technical University in Sofia in 2009. He is a student, M. Sc., in Department of Power Engineering and Electrical Equipment, University of Transport in Sofia, Bulgaria.